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Risk-based electric power system planning for climate change mitigation through multi-stage joint-probabilistic left-hand-side chance-constrained fractional programming: A Canadian case study

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A R T I C L E I N F O

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A B S T R A C T

Climate change mitigation by reducing greenhouse gas emissions is one of the major challenges for existing electric power systems. This study presents a multi-stage joint-probabilistic left-hand-side chance-constrained fractional programming (MJCFP) approach to help tackle various uncertainties involved in typical electric power systems and thus facilitate risk-based management for climate change mitigation. The MJCFP approach is capable of solving ratio optimization problems associated with left-hand-side random information by integrating multi-stage programming method, joint-probabilistic chance-constrained programming, fractional programming into a general framework. It can balance dual-objectives of two aspects reflecting system optimal ratio and analyze many of possible scenarios due to various end-user demand situations during different periods. The MJCFP approach is implemented and applied to the provincial electric power system of Saskatchewan, Canada to demonstrate its effectiveness in dealing with the tradeoff between economic development and climate change mitigation. Potential solutions under various risk levels are obtained to help identify appropriate strategies to meet different power demands and emission targets to the maximum extent. The results indicate that the MJCFP approach is effective for regional electric power system planning in support of long-term climate change mitigation policies; it can also generate more alternatives through risk-based management, which allows in-depth analysis of the interrelationships among system efficiency, system profit and system-failure risk.

1. Introduction

Earth's climate is warming owing to anthropogenic emissions of greenhouse gases (GHGs), particularly from fossil fuel combustion [1–3]. Almost all energy systems emit GHGs and contribute to climate change [4–6]. Especially, for electric power systems (EPS), satisfying the soaring power demand is a critical strategic goal, but it should be achieved by constructing and upgrading the least economically and environmentally costly power systems [7]. The global electricity supply sector accounts for the release to the atmosphere of over 7700 million tonnes of carbon dioxide annually 2100 Mt C / yr, being 37.5% of total CO_2 emissions [8], and is projected to surpass the 4000 Mt C level by 2020 [9]. A shift towards low-carbon electricity sources has been shown to be an essential element of climate-change mitigation strategies [10]. Consequently, planning of mitigation and adaptation strategies to climate change and power demand requires effective regionalized planning and decision-making behavior [11,12].

A great number of complexities exist in electric power system management [13,14]. The first challenge is to identify a trade-off between conflicting economic and environmental concerns. Achieving solutions to environmental problems that we face today requires long-term potential actions for sustainable development [15]. The second is associated with uncertainties in the system components and parameters. Uncertainties can be derived from related processes and activities (e.g., exploration/exploitation, conversion/processing, and supply/demand), human-induced imprecision or fuzziness, such as lack of available data and biased judgment (or preferences) in assigning priority factors (weighting levels) to multiple management objectives [16,17]. The third challenge is the reflection of dynamic characteristics over the long-term planning horizon. For example, the various

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electricity demands have long challenged electric power systems (EPS) planners and managers [18]. It is often influenced by many powerful and unpredictable factors, such as economy, generation technologies, fuel prices, and relevant policy [18]. Therefore, efficient mathematical programming techniques for planning EPS management and climate change mitigation under these complexities are desired.

In past decades, a great number of optimization methods have been developed for dealing with electric power system management problems [19–22] and climate change mitigation [23–25], such as fuzzy programming, stochastic programming and interval mathematical programming [26]. For example, Zhu et al. [23] developed a full-infinite interval-stochastic mixed-integer programming (FIMP) method for planning carbon emission trading. Hemmati et al. [27] proposed a constrained nonlinear mixed integer optimization programming for transmission expansion planning in an electricity market. In these methods, the use of scenarios to model uncertainties in planning models has become increasingly popular [28]. For instance, Dayhim et al. [29], and Kim et al. [30] used a scenario based approach to capture the uncertainty in our study. The multi-stage stochastic programming (MSP) method was found to be effective in reflecting uncertainties expressed as random variables with known probabilities, which permitted revised decisions at each time stage according to the sequential realized uncertain issues [31,32]. Therefore, a number of multi-stage stochastic programming (MSP) methods were developed as extensions of dynamic stochastic optimization methods to deal with system dynamic features [33–35]. Although MSP is suitable for solving long-term planning problems, it is incapable of accounting for the risk of violating joint-probabilistic constraints within a complicated electric power system [36]. Improving upon the conventional right-hand-side chance-constrained programming, joint-probabilistic left-hand-side chance-constrained programming can not only reflect left-hand-side random variables (the relationship between carbon emissions and power generation amounts) but also examine the risk of violating the system constraints [37], especially the risk of high carbon emissions.

However, practical electric power system management and climate change mitigation activities often relate to multiple economic and environmental objectives which may be conflicting with each other, and MSP cannot identify a balanced decision among those conflicting objectives. Multi-objective programming models are helpful to deal with these problems, but most of the previous studies simply translated environmental targets into constraints, where the objective function was purely economic [38,39]; others assumed that environmental impacts could be evaluated as costs and thus converted all units into objective item [21,40,41]. As an effective measure to balance conflicting objectives, fractional programming (FP) may better fit real world problems by taking the optimization of the ratio between the physical and economic quantities into consideration [42]. For example, Zhu et al. [43] suggested that treating multiple economic and environmental objectives as a least-cost linear programming (LP) frame may not reflect the complexities of an environmental sustainability perspective. This indicates a fractional programming, as an alternative method for dealing with multi-objective problems, is practically suitable to achieve desired solutions related to system efficiency.

Therefore, a multi-stage joint-probabilistic left-hand-side chance-constrained fractional programming (MJCFP) approach will be proposed in this study to help tackle various uncertainties involved in typical electric power systems and thus facilitate risk-based management for climate change mitigation. In detail, fractional programming will be first incorporated within an MSP framework to address multiobjective issues. Joint-probabilistic chance-constrained programming will then be introduced to tackle stochastic problems associated with left-hand side random variables and reflect the risk of violating system carbon emission constraints under uncertainty. The MJCFP approach can balance dual-objectives of two aspects reflecting system optimal ratio and analyze many of possible scenarios due to various end-user demand situations during different periods. It thus can help decision-makers identify the optimal electric power system management strategies and gain deeper insights into system efficiency, system profit and system-failure risk under different GHG emission targets. The proposed approach will be further implemented and applied to the provincial electric power system of Saskatchewan, Canada to demonstrate its effectiveness in dealing with the tradeoff between economic development and climate change mitigation.

2. Saskatchewan electric power system

2.1. Overview

As Saskatchewan's economy and population continue to grow, so does the need for electricity which takes power to grow. Saskatchewan electricity sales volumes are expected to increase by 29% over the next ten years [44]. Provincial load growth forecasts indicate the need for an additional 5929 GWh over the next decade [44]. The principal electric utility in Saskatchewan manages a net generating capacity of 3451 MW that includes hydro (21%), thermal coal (41%), thermal gas (33%), and wind (5%) by operating three coal-fired power stations, seven hydroelectric stations, six natural gas stations, and two wind facilities [45]. The system is illustrated in Fig. 1. These energies are consumed by the residential, farm, commercial, oilfield, power and reseller sectors. During the next decade, the system peak demand is expected to increase by approximately 2.2% per year, double the 1.1% per year recorded between 2000 and 2010 [44]. Three conventional coal-fired power plants comprise 1682 MW of this capacity being used to meet base load needs. The generation capacity of natural gas facilities, hydro facilities, wind facilities and cogeneration facilities are 813 MW, 853 MW, 161 MW and 438 MW [46]. From a long-term planning point of view, the planning horizon of this study is 15 years with three planning periods, from 2015 to 2030.

In 2010, Saskatchewan's GHG emissions were 69.8 t/capita (t/c), about 3.5 times the national average [45]. The electricity sector comprises 22% of the province's GHG emissions. Thus, the fact that Saskatchewan's electricity sector accounts for significant emissions must be viewed and considered in the study that Saskatchewan's greenhouse gas emissions are unacceptably high. These power stations pose two challenges for the provincial electric power system: they are very significant GHG emitters and, they are reaching the end of their useful life. Especially, new federal regulations took effect on July 1, 2015, that significantly impacted coal fleet in Saskatchewan. The performance standard for new coal-fired electricity generation units in Canada is supposed to be 420 t/GWh [44]. New and end-of-life units that incorporate technology for carbon capture and storage (CCS) might apply for an exemption from the performance standard until 2025 [47]. The decisions required of SaskPower by concerning investments in replacement generating facilities, simultaneously, meeting burgeoning demand for additional power will set the course for the corporation for coming decades.

2.2. Statement of problems

Electric utilities in Saskatchewan operate in the second largest service area in Canada and has the lowest customer density of any Canadian utility [44]. These electric utilities is committed to supporting economic growth in the province through the delivery of reliable, affordable and sustainable power to Saskatchewan's people, as customers, business owners, and residents, to give them the power to live well [48]. Like any electrical utility in other areas, the system faces many challenges, not the least of which is adapting to a future that includes significant changes in climate and international, as well as local, responses to those changes. Saskatchewan's electric utilities also have adaptation opportunities that could benefit the province, both from economic and climate change mitigation.

In the Saskatchewan electric power system, there are significant

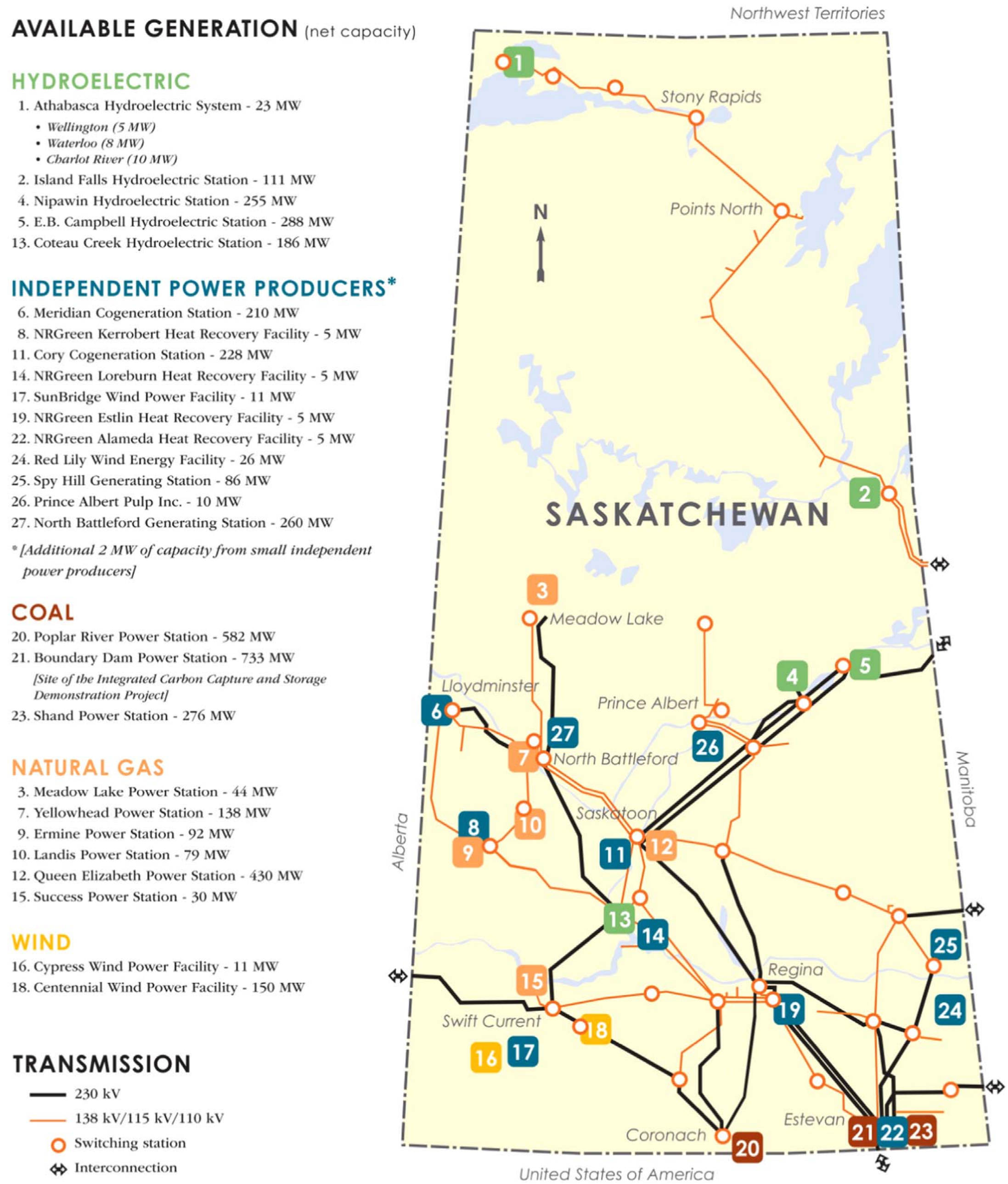

Fig. 1. Saskatchewan electric power system.

variations in power demand and supply, electricity generation processes and related economic parameters and errors. In addition, there are complexities would be further intensified due to the uncertainties in the objective function and constraints, and capacity expansion schemes for electricity generation units to satisfy the continuing increments of demand. Accordingly, the energy demand of different customer sectors may vary from each period under the different economic conditions, which can be expressed as random variables. Moreover, it is generally either technically infeasible or economically impossible to design processes leading to zero emissions of carbon. Consequently, under different probability levels of constraint violation, uncertainties, dynamic and random information will exist in electric power system management during periods.

Thus, an effective long-term planning for decision makers in Saskatchewan is highly desired with a comprehensive consideration given to these complexities and uncertainties. The problem under consideration is how to effectively identify electricity generation, allocation and capacity expansion schemes to achieve both economic and environmental goals. The challenges of the study include: (i) how to effectively generate and allocate power to meet demands of end-user sectors; (ii) how to deal with the uncertainties and random information existing in both the objective and constraints; (iii) how to identify feasible capacity expansion schemes for electricity generation units; (iv) how to maximize system profit with potential low carbon emissions; and (v) how to handle the tradeoff between system objective and reliability. This discussion paper is aimed at reviewing the SaskPower system and identify specific strategies and opportunities.

3. Development of the MJCFP model

3.1. Methodology

A decision maker is responsible for identifying power supply and allocation, facility expansion and carbon mitigation schemes with a

maximized system profit in a multi-period horizon. In the system, the power demands of different end-user sectors may vary from each period. These can be expressed as random variables, and the dynamics of the study system can be formulated through a multi-stage programming (MSP) approach. Thus, in an MSP model for the electric power system management, the objective is to maximize system profit while satisfying the total carbon emission requirement. System profit is the difference between total revenue and total cost. Specifically, the economic objective can be formulated as follows [49]:

$$Maxf = \sum_{1}^{T} C_t X_t - \sum_{1}^{T}\sum_{1}^{Q_t} p_{tq} D_{tq} Y_{tq} \tag{1a}$$

subject to:

$$A_{rt} X_t \le B_{rt} \tag{1b}$$

$$A_{rt} X_t + A'_{rt} Y_{tq} \le w_{rtk},\ \ i = 1, 2, \ldots, m_2;\ t = 1, 2, \ldots, T;\ q = 1, 2, \ldots, Q_t \tag{1c}$$

$$x_{jt} \ge 0,\ \ x_{jt} \in X_t, j = 1, 2, \ldots, n_1;\ t = 1, 2, \ldots, T \tag{1d}$$

$$y_{jtq} \ge 0,\ \ y_{itq} \in Y_{tq}, j = 1, 2, \ldots, n_2;\ t = 1, 2, \ldots, T;\ q = 1, 2, \ldots, Q_t \tag{1e}$$

where X_t and Y_{tq} are decision variables; C_t are coefficients of recourse variables (X_t) in the objective function; p_{tq} is probability of occurrence for scenario q in period t, with $p_{tq} \ge 0$ and $\sum_1^{Q_t} p_{tq} = 1$; D_{tq} are coefficients of recourse variables (Y_{tq}) in the objective function; A'_{rt} are coefficients of Y_{tq} in constraint i; w_{rtk} is random variable of constraint i, which is associated with probability level p_{tq}; Q_t is number of scenarios in period t, with the total being $Q = \sum_1^T Q_t$. In model (1), the decision variables are divided into two subsets: those that must be determined before the realizations of random variables are disclosed (i.e., x_{jt}), and those (recourse variables) that can be determined after the realized random variable values are available (i.e, y_{jtq}).

Obviously, the model (1) can deal with uncertainties in the right-hand sides presented as random variables in the objective function, expressed as random variables with known distributions with known probability distributions. Nevertheless, in daily electric power system management problems, we must tackle the environmental objectives related to carbon emissions and randomness in the constraints' left-hand sides. For example, uncertainties presented in terms of joint probabilities may exist in carbon emissions in different periods. The emission target may be fixed to a level of probability, which represents the admissible risk of violating the uncertain emission constraints. Such uncertainties could lead to complexities in power generation where interactive and dynamic relationships exist within a multistage context. The technique of joint probabilistic left-hand-side chance-constrained programming (JLCP) can be used for dealing with such complexities [37]. A general JLCP formulation can be expressed as [37]:

$$Maxf = \sum_{j=1}^{n} c_j x_j \tag{2a}$$

Subject to:

$$\Pr\left\{\sum_{j=1}^{n} a_{ij}(\omega) x_j \le b_j\right\} \ge 1 - p_i, \quad i = 1, 2, \ldots, m \tag{2b}$$

$$\sum_{i=1}^{m} p_i \le p \tag{2c}$$

$$a_{ij}(\omega) \sim N(\mu_{ij}, \sigma_{ij}^2) \tag{2d}$$

$$x_j \ge 0,\ \ j = 1, 2, \ldots, n \tag{2e}$$

where f is an objective function; x_j are decision variables; b_j and c_j are coefficients of recourse variables (x_j) in the objective function and constraints; a_{ij} are random left-hand parameters in constraints; and $1 - p$ is a prescribed joint probability level at which the entire set of uncertain constraints is enforced to be satisfied.

However, the trade-off in conflicting objectives between system economic profit and climate change mitigation needs to be reflected. Such complexities cannot be reflected in the above models. Fortunately, the linear fractional programming (LFP) method can be effective in balancing two conflicting objectives and addressing randomness in the right-hand parameters [43]. A general linear fractional programming (LFP) problem can be formulated as follows:

$$Maxf(x) = \frac{CX + \alpha}{DX + \beta} \tag{3a}$$

subject to

$$AX \le B \tag{3b}$$

$$X \ge 0 \tag{3c}$$

where X is a decision variable; A is a real $m \times n$ matrix; X and B are column vectors with n and m components respectively; C and D are row vectors with n components; α and β are constants. Charnes and Cooper [50] showed that if the denominator is constant in sign for all X in the feasible solution area, the LFP model can be optimized by solving a linear programming problem. The LFP model (3) can tackle deterministic optimal ratio problems.

Although Model (1) can reflect uncertainties in the power demands during different periods, with power demand being presented as random variables, two more extended considerations are: (i) the optimal ratio problem; (ii) uncertainties existing in the left-hand parameters. Consequently, through introducing the LFP technique, the joint probabilistic left-hand-side CCP method, and mixed-integer linear programming techniques into the MSP framework, the combined method will address both of these extended considerations.

This leads to an MJCFP model as follows:

$$Maxf = \frac{\sum_1^T C_t X_t - \sum_1^T \sum_1^{Q_t} p_{tq} D_{tq} Y_{tq}}{\sum_1^T \sum_1^{Qt} E_{tq} Y_{tq}} \tag{4a}$$

subject to:

$$A_{rt} X_r \le B_{rt} \tag{4b}$$

$$A_{rt} X_r + A'_{rt} Y_{tq} \le w_{rtk},\ \ i = 1, 2, \ldots, m_2;\ t = 1, 2, \ldots, T;\ q = 1, 2, \ldots, Q_t \tag{4c}$$

$$\Pr\left\{\sum_{j=1}^{n} a_{ij}(\omega) x_j \le b_j\right\} \ge 1 - p_i,\ \ i = 1, 2, \ldots, m \tag{4d}$$

$$\sum_{i=1}^{m} p_i \le p \tag{4e}$$

$$a_{ij}(\omega) \sim N(\mu_{ij}, \sigma_{ij}^2) \tag{4f}$$

$$x_{jt} \ge 0,\ \ x_{jt} \in X_t, j = 1, 2, \ldots, n_1;\ t = 1, 2, \ldots, T \tag{4g}$$

$$y_{jtq} \ge 0,\ \ y_{itq} \in Y_{tq}, j = 1, 2, \ldots, n_2;\ t = 1, 2, \ldots, T;\ q = 1, 2, \ldots, Q_t \tag{4h}$$

$$x_{jt} \ge 0,\ \ x_{jt} \in X_t, \text{ and } x_{jt} = \text{integer varibles};\ \ j = n_1 + 1, n_1 + 2, \ldots, m_1;\ t = 1, 2, \ldots, T;\ q = 1, 2, \ldots, Q_t \tag{4g$'$}$$

$$y_{jtq} \ge 0,\ \ y_{itq} \in Y_{tq}, \text{ and } y_{itq} = \text{integer varibles};\ \ j = n_2 + 1, n_2 + 2, \ldots, m_2;\ t = 1, 2, \ldots, T;\ q = 1, 2, \ldots, Q_t \tag{4h$'$}$$

where X_t and Y_{tp} are decision variables; C_t are coefficients of variables X_t; D_{tq} and E_{tq} are coefficients of variables Y_{tp}; a_{ij} are random left-hand parameters in constraints.

According to Sun et al. [37], a sufficient condition for solving Eq. (4d) is to solve as

$$\sum_{j=1}^{n} [x_j(\mu_{ij} + \sigma_{ij}\phi^{-1}(1 - p_i))] \leq b_j, \forall\ i \tag{4i}$$

Moreover, according to the LFP method presented in Chadha and Chadha [51], if (1)

$$\sum_{1}^{T} \sum_{1}^{Qt} E_{tq} Y_{tq} > 0 \tag{4j}$$

for all feasible X and Y, (2) the objective function is continuously differentiable, and (3) the feasible region is nonempty and bounded, then the MJCFP model could be solved through a linear programming approach.

The specific solution process for the MJCFP model is shown as follows:

- Step 1: Identify and collect the uncertain variables and the related possibility distribution information;
- Step 2: Build the original MJCFP Model (4).
- Step 3: Transform stochastic constraints [Eq. (4d)] into deterministic constraints [Eq. (4i)] under a specific significance level (p_i) for the constraint i.
- Step 4: Solve the transformed model through the linear fraction programming method.
- Step 5: Repeat Steps 3–4 under different p_i levels.

Hence, the proposed MJCFP approach consists of a ratio objective and a set of constraints according to the environmental policy and power demand, where randomness in both the objective and constraints with known probability distributions can be addressed. The developed MJCFP approach is effective in dealing with electric power system management and climate change mitigation problems, where an analysis of policy scenarios is desired and the related data are mostly uncertain.

3.2. Model formulation

The developed MJCFP approach is employed in this study for electricity management in Saskatchewan. The objective is to maximize the ratio of system profit to carbon emissions through optimal solutions. Therefore, the application of the MJCFP approach in an EPS management scheme is critical for: (1) satisfying all the end-user power demand requirements; (2) recognizing appropriate electricity generation and allocation plans; (3) maximizing the ratio of economic profit to carbon emissions; (4) identifying specific capacity expansion solutions; (5) mitigating climate change under different risk levels. Therefore, the proposed MJCFP approach is considered suitable for tackling such a problem. In detail, the system revenue and cost of the Saskatchewan EPS model is formulated as a sum of the following elements:

1) Electricity sales revenue

$$f_1 = \sum_{1}^{T} \sum_{1}^{D} \sum_{1}^{Q_t} p_q \cdot RE_{td} \cdot XDEM_{tdq} \tag{5-1a}$$

2) Electricity export revenue

$$f_2 = \sum_{1}^{T} \sum_{1}^{Q_t} p_q \cdot REE_{tq} \cdot XEE_{tq} \tag{5-1b}$$

3) Byproducts revenue

$$f_3 = \sum_{1}^{T} \sum_{1}^{B} RP_{tb} \cdot PR_{tb} \tag{5-1c}$$

4) Cost for fuel supply

$$f_4 = \sum_{1}^{T} \sum_{1}^{J} \sum_{1}^{Q_t} p_q \cdot COF_{tj} \cdot X_{tjq} \tag{5-1d}$$

5) Cost for electricity generation

$$f_5 = \sum_{1}^{T} \sum_{1}^{J} \sum_{1}^{Q_t} p_q \cdot VAC_{tj} \cdot X_{tjq} + \sum_{1}^{T} \sum_{1}^{J} FIX_{tj} \cdot (RED_{tj} + YP_{(t-1)jm} \cdot XC_{(t-1)jm} - RET_{tj}) \tag{5-1e}$$

6) Cost for transmission and distribution

$$f_6 = \sum_{1}^{T} \sum_{1}^{J} \sum_{1}^{Q_t} p_q \cdot TR_{tj} \cdot X_{tjq} \tag{5-1f}$$

7) Cost for capacity expansions

$$f_7 = \sum_{1}^{T} \sum_{1}^{J} \sum_{1}^{M} XC_{tjm} \cdot YP_{tjm} \cdot INC_{tj} \tag{5-1g}$$

8) Cost for import electricity from other electric power systems

$$f_8 = \sum_{1}^{T} \sum_{1}^{Q_t} p_q \cdot COI_t \cdot XEI_{tq} \tag{5-1h}$$

Thus, the ratio objective of MJCFP approach can be formulated as follows:

$$Maxf = \frac{\text{SystemProfit}}{\text{CarbonEmissionAmount}} = \frac{f_1 + f_2 + f_3 - f_4 - f_5 - f_6 - f_7 - f_8}{\sum_1^T \sum_1^J \sum_1^{Q_t} p_q \cdot EM_{tj} \cdot X_{tjq}} \tag{5-1}$$

The constraints of the model are defined as follows:

1. Mass balance constraints

$$\sum_{1}^{J} X_{tjq} + XEI_{tq} \geq \sum_{1}^{D} XDEM_{tdq} + \sum_{1}^{J} LOSS_{tjq} + XEE_{tq} \quad \forall\ t, q \tag{5-2a}$$

2. End-user demand constraints

$$\eta_{tq} \cdot DEM_{td} \cdot (1 + \alpha_t) \geq XDEM_{tdq} \quad \forall\ t, d, q \tag{5-2b}$$

$$\eta_{tq} \cdot DEM_{td} \leq XDEM_{tdq} \quad \forall\ t, d, q \tag{5-2c}$$

3. Base load demand constraints

$$\sum_{1}^{J} (X_{tjq} - LOSS_{tjq}) \geq \beta_t \cdot \eta_{tq} \cdot \sum_{1}^{D} DEM_{td} \quad \forall\ t, q \tag{5-2d}$$

4. Peak load demand constraints

$$\sum_{1}^{J} (RED_{tj} + XC_{(t-1)jm} \cdot YP_{(t-1)jm} - RET_{(t-1)j}) \geq PL_t \quad \forall\ t \tag{5-2e}$$

5. Capacity constraints for electricity generation

$$X_{tjq} \leq (RED_j + \sum_{1}^{T} \sum_{1}^{M} YP_{(t-1)jm} \cdot XC_{(t-1)jm} - \sum_{1}^{T} RET_{(t-1)j}) \cdot CF_j \cdot L_t \quad \forall\ t, j, q \tag{5-2f}$$

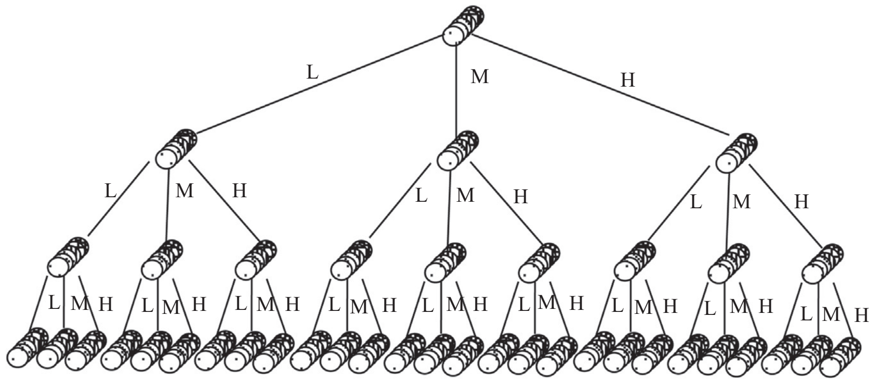

Fig. 2. Scenario tree for electric power system planning.

Table 1
Scenarios at representative joint and individual probabilities.

Condition	p_k	p_1	p_2	p_3
1	0.01	0.001	0.003	0.006
2		0.003	0.006	0.001
3		0.006	0.001	0.003
4	0.05	0.01	0.015	0.025
5		0.015	0.025	0.01
6		0.025	0.01	0.015
7	0.1	0.02	0.03	0.05
8		0.03	0.05	0.02
9		0.05	0.02	0.03

$$XEE_{tq} \le UEE_t \quad \forall\ t,\ q \tag{5-2g}$$

$$XEI_{tq} \le UEI_t \quad \forall\ t,\ q \tag{5-2h}$$

6. Capacity expansion

$$RED_{tj} + \sum_{1}^{T}\sum_{1}^{M} YP_{(t-1)jm}\cdot XC_{(t-1)jm} - RET_{(t-1)j} \le UXC_{tj} \quad \forall\ t,\ j \tag{5-2i}$$

7. Expansion options

$$\sum_{1}^{M} YP_{tjm} \le 1 \quad \forall\ t,\ j \tag{5-2j}$$

$$YP_{tjm} = 0 \text{or} 1 \tag{5-2k}$$

8. CO_2 emission permits

$$\Pr\left\{\begin{array}{l} \sum_1^J EM_j^{(p_s)}\cdot X_{1jq} \le ET_1,\ \ t = 1, \forall\ q \\ \sum_1^J EM_j^{(p_s)}\cdot X_{2jq} \le ET,\ t = 2, \forall\ q \\ \sum_1^J EM_j^{(p_s)}\cdot X_{3jq} \le ET_3,\ t = 3, \forall\ q \end{array}\right\} \ge 1 - p_k \quad \forall\ k \tag{5-2l}$$

9. Byproducts sell limit constraints

$$PR_{tb} \le TP_{jb}\cdot X_{tj} \quad \forall\ t,\ j,\ b \tag{5-2m}$$

10. Nonnegative constraints

$$X_{tjq},\ XDEM_{tdq},\ XEE_{tq},\ XEI_{tq},\ PR_{tb} \ge 0 \quad \forall\ t,\ j,\ q,\ d,\ b \tag{5-2n}$$

where:
Decision variables

X_{tjq} = electricity generation amount by power j under scenario q in period t (GWh)

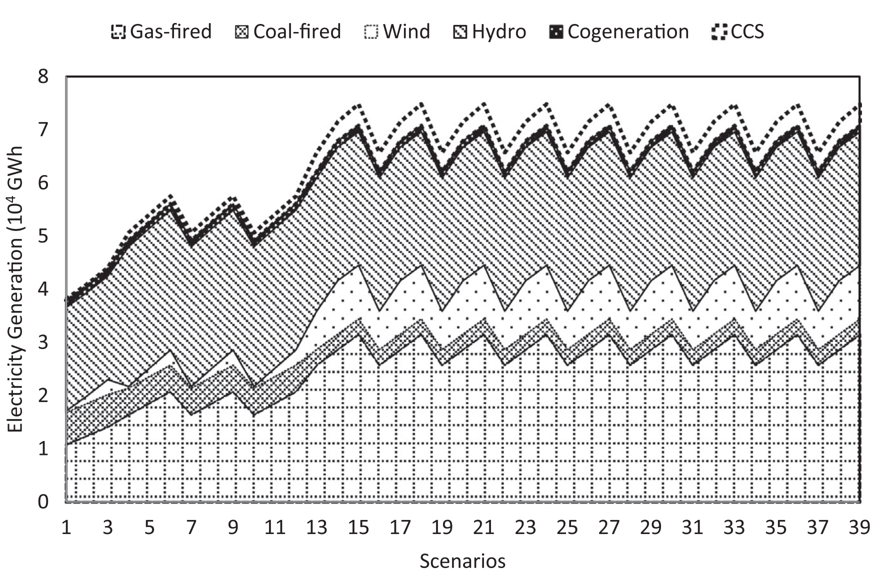

Fig. 3. Solutions of electricity generation plan for electric power plants under $p_k = 0.1$ (condition 8).

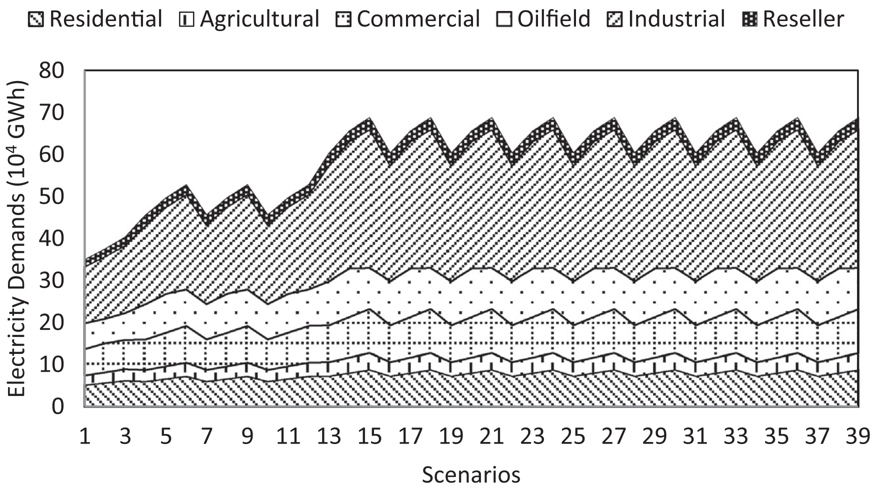

Fig. 4. Solutions of power allocation plan for end-user sectors under $p_k = 0.1$ (condition 8).

$XDEM_{tdq}$ = electricity supply for demand user d under scenario q in period t (GWh)

XEE_{tq} = electricity export amount under scenario q in period t (GWh)

XEI_{tq} = electricity import amount under scenario q in period t (GWh)

YP_{tjm} = capacity expansion option of power type j under different expansion program m in period t (GWh)

Parameters

t = time period, $t = 1, 2, 3.$

d = demand user, $d = 1, 2, \ldots, 6$ (where $d = 1$ for residential user, $d = 2$ for agricultural user, $d = 3$ for commercial user, $d = 4$ for oilfield user, $d = 5$ for industrial user, $d = 6$ for reseller user)

q = demand scenario, (when $t = 1$, $q = 1, 2, 3$; when $t = 2$, $q = 1, 2, \ldots, 9$; when $t = 3$, $q = 1, 2, \ldots, 27$)

j = electricity power generation types, $j = 1, 2, \ldots, 6$ (where $j = 1$ for gas−fired power, $j = 2$ for coal−fired power, $j = 3$ for wind power, $j = 4$ for hydro power, $j = 5$ for cogeneration power, $j = 6$ for carbon capture and storage)

m = capacity expansion plan, $m = 1, 2, 3$, each power generation technology provided with three expansion options

p_q = probability of occureence of scenario q

p_k = jointprobability of violating constraints of the emission target

RE_{td} = electricity price for demand user d in period t ($/MWh)

REE_{tq} = electricity export price under scenario q in period t ($/MWh)

RP_{tb} = unit revenue of byproduct b in period t ($/tonne)

COF_{tj} = cost of fuel for generation type j in period t ($/MWh)

VAC_{tj} = variable cost of operation and maintenance for generation type j in period t ($/MWh)

FIX_{tj} = fixed cost of operation and maintenance for generation type j in period t ($/MW)

RED_{tj} = current capacity of generation type j in period t (MW)

XC_{tjm} = capacity option m for generation type j in period t (MW)

RET_{tj} = retirement capacity of generation type j in period t (MW)

TR_{tj} = cost of transmission and distribution for generation type j in period t ($/MWh)

INC_{tj} = investment cost of capacity expansion for power type j in period t ($/MW)

COI_t = electricity import cost in period t ($/MWh)

EM_{tj} = carbon emissions intensity of generation type j in period t (tonne /MWh)

$LOSS_{tjq}$ = electricity loss of generation type j under scenario q in period t (MWh)

DEM_{td} = forecast electricity demand of end−user d in period t

η_{tq} = demand level under scenario q in period t (where $\eta_{tq} = 0.9$ for low level, $\eta_{tq} = 1.0$ for middle level, $\eta_{tq} = 1.1$ for high level)

α_t = the maximum receive amount for demand users in period t (%)

β_t = baseload rate of electricity demand in period t (%)

PL_t = peakload of electricity demand in period t (MW)

CF_j = capacity factor of generation type j (%)

L_t = time length of period t (hours)

UEE_t = maximum electricity export amount in period t (MW)

UEI_t = maximum electricity import amount in period t (MW)

UXC_{tj} = maximum capacity of generation type j in period t (MW)

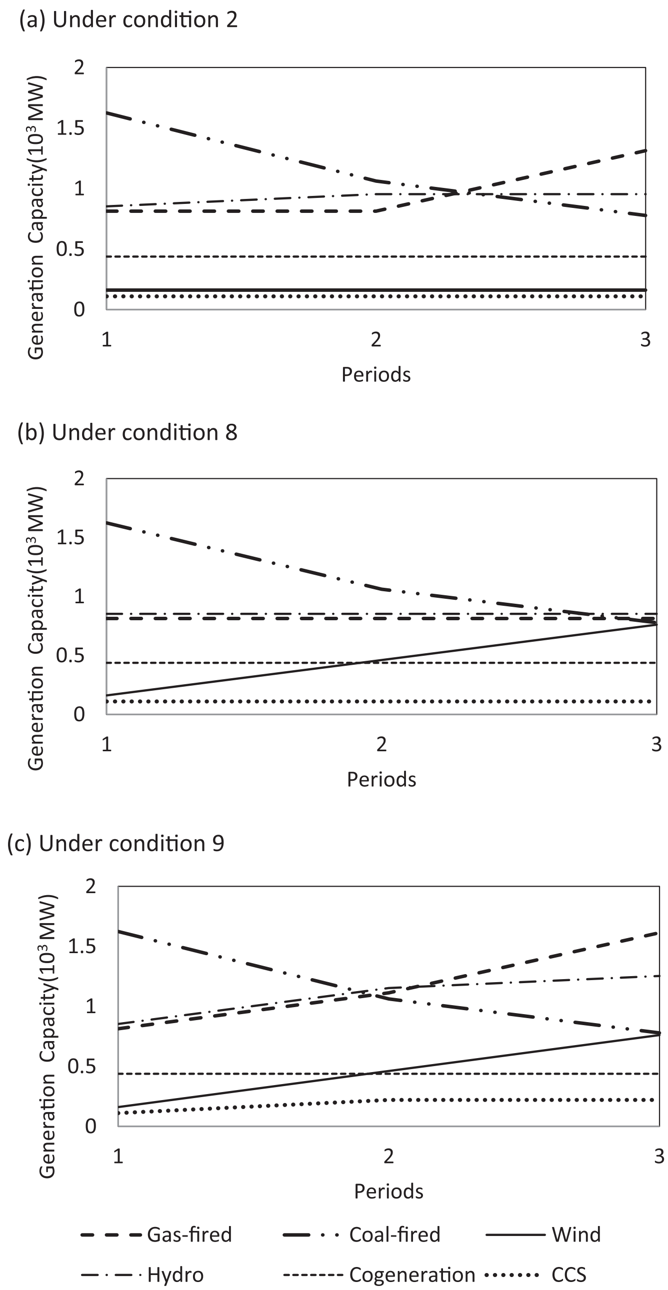

Fig. 5. Solutions of capacity expansion scheme for electric power plants under $p_k = 0.01$ (condition 2), $p_k = 0.1$ (condition 8, condition 9).

ET_t = carbon emssion target in period t (tonne)

TP_{jb} = productionrate of byproduct b by generation type j (tonne/MWh)

4. Results and discussion

In this case, the multilayer scenario tree with a branching structure can be constructed for reflecting random end-user power demands, which results in three scenarios in period 1, nine scenarios in period 2, and twenty-seven scenarios in period 3 (shown in Fig. 2). In addition, a set of chance constraints for the carbon emissions target for the three periods are considered, which can help investigate the risk of violating the emission permit constraints and generate desired power allocation and generation schemes. Nine conditions (i.e. nine EPS models) are examined based on multiple joint probabilities and individual probabilities. Three increasing joint probabilities (0.01, 0.05 and 0.1, in Table 1) indicate an increased risk of violating the constraints of carbon emission target. At each level of joint probability, there were three sets of individual probabilities (i.e. condition 1, 2 and 3). Consequently, for each risk level, there were 39 scenarios to be examined over three planning periods.

Fig. 3 reveals that the electricity generation plans under $p_k = 0.1$ (i.e. condition 8 listed in Table 1). For example, when demand levels are low (probability = 20%) in the period 1, the amounts of power generated by gas-fired power, coal-fired power, wind power, hydropower, cogeneration power and CCS during the period 1 would be 10856.59, 6046.15, 282.07, 19427.92, 1170.25 and 409.53 GWh. When demand levels are high in period 1, the generation amounts of six power generation types would be 14237.14, 6046.15, 2820.72, 19427.92, 1170.25 and 409.53 GWh. It indicates that gas-fired power and wind power are two main sources to respond to electricity demand variation. Moreover, based on low demand levels in the first period, amounts of power generated by six conversion technology types would be 18681.82, 5003.711, 1567.67, 26266.75, 1170.25 and 1451.97 GWh when the demand levels are middle in period 2. Generally, generation amounts of different power types are increasing in order to meet power demands. However, coal-fired power generation decreases because there are several coal-fired plants being retired owing to new federal carbon mitigation regulations.

In addition, the MJCFP model also provides the solution of power allocation plan for six end-user sectors under $p_k = 0.1$ shown in Fig. 4(i.e. condition 8). Under the highest demand scenario (i.e. when power demands are all at high levels during the entire panning horizon), the power allocation for residential, agricultural, commercial, oilfield, industrial and reseller sector would be 6308.45, 2718.47, 6906.81, 6405.09, 16114.98 and 1985.49 GWh in period 1, 7343.56, 3261.42, 8673.49, 8722.05, 22545.50 and 2298.23 GWh in period 2, 8870.72, 3996.22, 10469.05, 9667.39, 33028.04 and 2764.58 GWh in period 3. The results indicate that power consumption of Saskatchewan customers would grow steadily over the 15 years planning horizon due to rapid population growth and economic development.

The results show that any change in p_k would yield varied carbon emissions and thus results in varied management schemes, especially in capacity expansion patterns. Fig. 5 provides the illustrate the optimized expansion pattern under condition 2 (when $p_k = 0.01$), 8 and 9 (when $p_k = 0.1$). Under condition 8, existing capacities of wind power might be insufficient to meet energy demands. The wind power facilities would be expanded with a capacity of 300 MW in period 1 and another 300 MW in period 2, which are different from those under condition 2. In comparison, under condition 2, a capacity of 100 MW would be added to the hydropower facilities in period 1, while gas-fired generation technology would be expanded with a capacity of 500 MW in period 2. Moreover, the expansion plans would vary with individual probability (p_s) of each carbon emission constraint (even under same joint probability level). For example, the joint probability level of condition 9 is 0.10, and its individual probabilities in period 1, 2 and 3 are 0.05, 0.02 and 0.03. The optimized expansion plans under condition 9 is also shown in Fig. 5.

Generally, the MJCFP approach results also indicate that a higher p_k level would correspond to a higher optimal ratio at the cost of environment. For example, with p_k rising from 0.01 to 0.1, the ratio objective under condition 1 (when $p_k = 0.01$), condition 4 (when $p_k = 0.05$) and condition 7 (when $p_k = 0.1$) would increase as 128.67, 131.05, 133.60 \$/(tonne emission), while the system profit would be $\$7.24 \times 10^9$, $\$7.25 \times 10^9$ and $\$7.32 \times 10^9$, and the carbon emissions would be 56.30, 55.28 and 54.80 Mt ($1\ \text{Mt} = 10^6\ \text{t}$). Thus, the relationship between the objective ratio and uncertain conditions demonstrates a trade-off between objective ratio and constraint violation under all possible scenarios. An increased p_k level represents a higher admissible risk, leading to an increased strictness for the constraints and hence an expanded decision space. Consequently, with a growing risk of carbon emission target violation, an alternative corresponding to

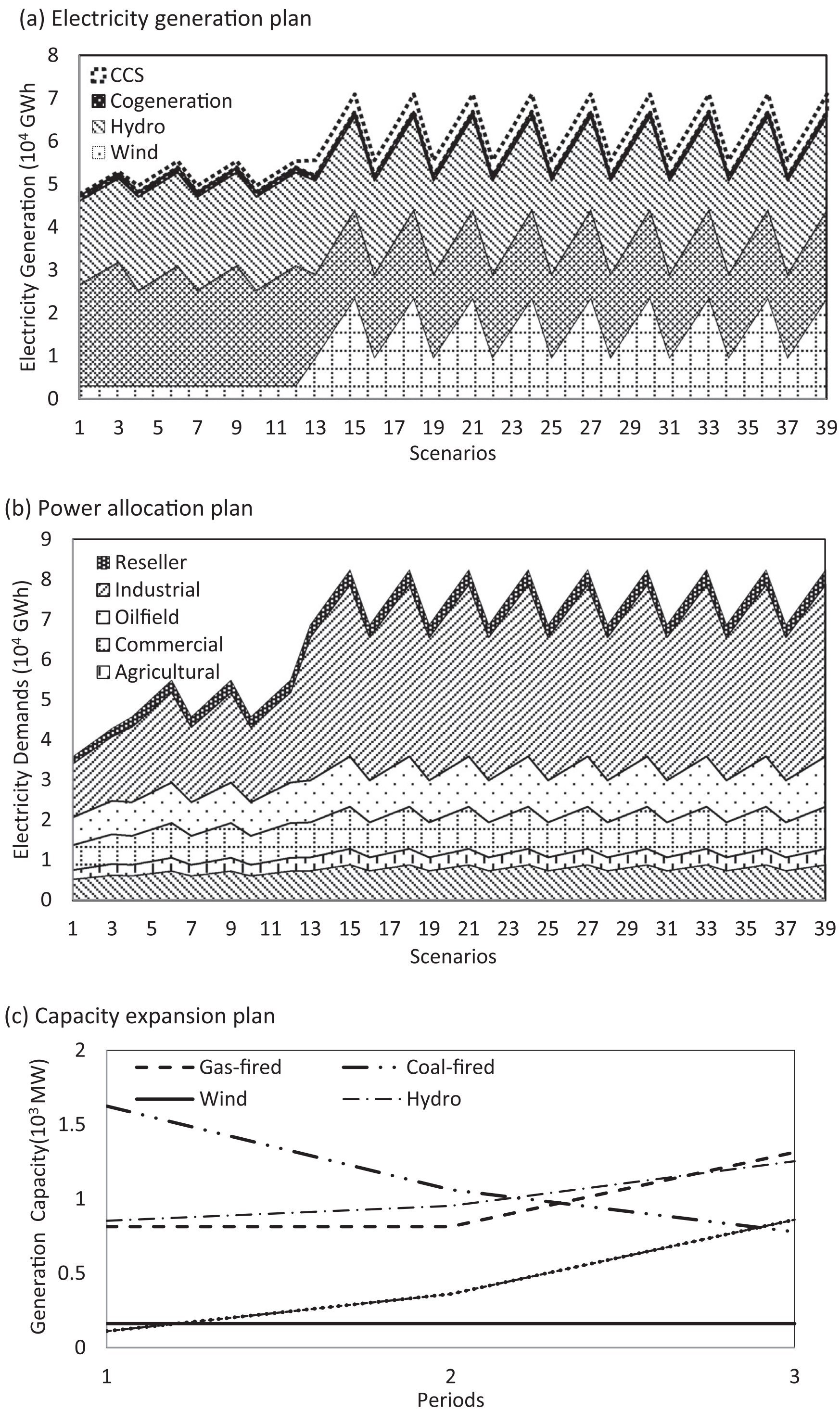

Fig. 6. Solutions of MJCLP model for electric power system management plan under $p_k = 0.1$ (condition 8).

higher optimal ratio is obtained. While planning under a lower p_k level, this will result in a corresponding situation with a higher reliability but a lower optimal ratio. The above results demonstrate that the MJCFP approach can solve problems with stochastic and dynamic information under the modeling framework, and provide a range of solutions with associated system failure risk levels. The approach can also support in-depth analysis of the interrelationship between system optimal ratio and climate change risk.

When Saskatchewan decision makers place more emphasis on economic aspects and aim towards maximizing system profit, the optimal ratio problem shown in Model (6) can be changed into a maximum profit problem by replacing Eq. (6a) with the following objective:

$$Maxf = \text{SystemProfit} = f_1 + f_2 + f_3 - f_4 - f_5 - f_6 - f_7 - f_8 \quad (6m)$$

The generated model is a multi-stage joint-probabilistic left-hand-side chance-constrained linear programming (MJCLP) problem subject to Eqs. (5-2a) to (5-2n). Therefore, results under different p_k levels can be obtained with the same parameter settings for stochastic uncertainty. Fig. 6 provides the MJCLP solutions of electricity generation and allocation plan, and capacity expansion scheme for Saskatchewan decision makers under condition 8. The power generation and allocation plans obtained from the MJCLP and optimal ratio models are generally different. Due to pursuing higher economic competitiveness,

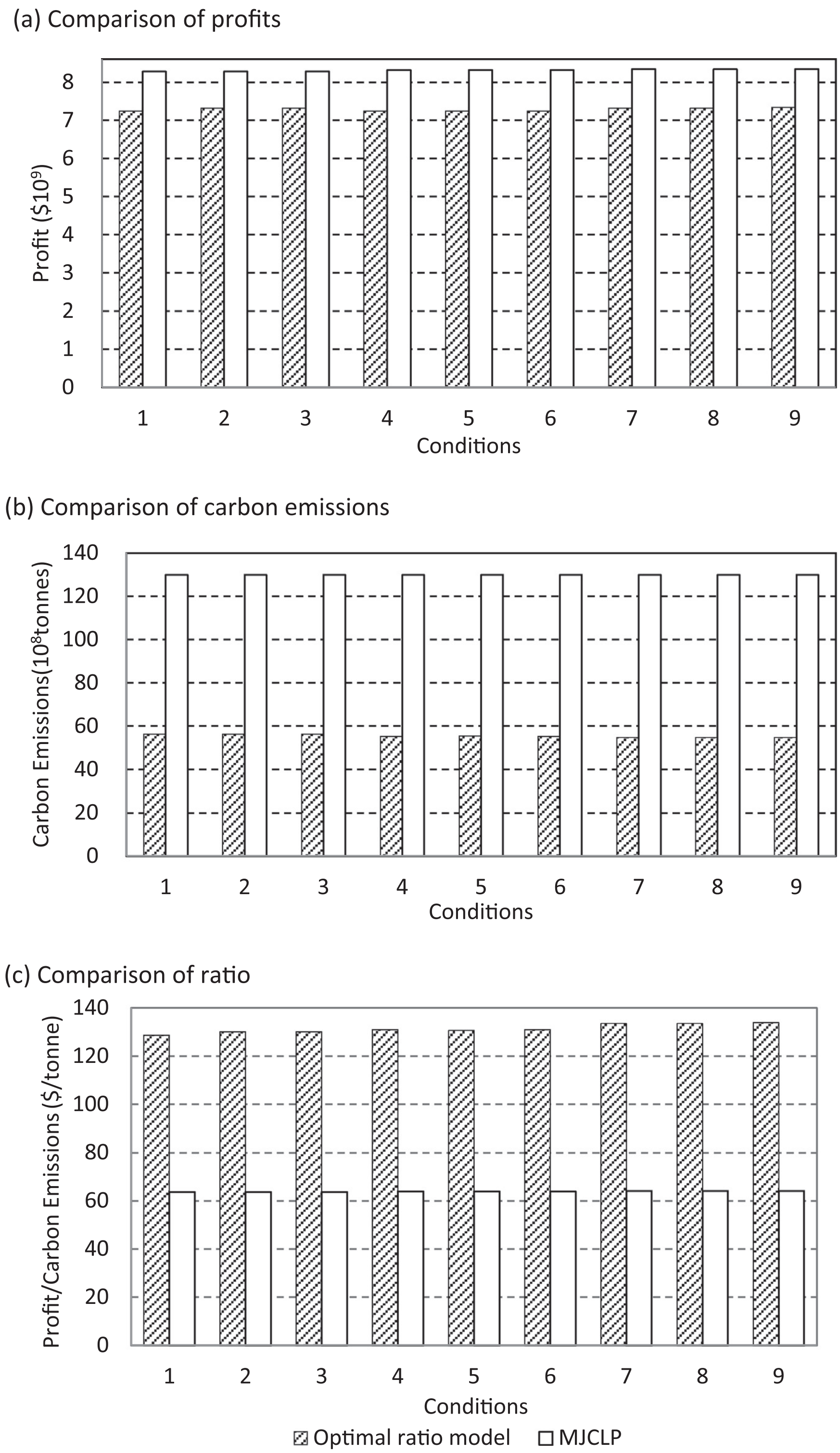

Fig. 7. Comparison between optimal ratio and MJCLP under p_k = 0.01, 0.05, 0.1.

coal-fired power becomes the main electricity generation type, although its carbon emissions intensity is much stronger than other types. For example, under the biggest demand scenario, the power generation of gas-fired power, coal-fired power, wind power, hydropower, cogeneration power and CCS would be 3098.02, 28578.92, 282.07, 19427.93, 1170.25 and 4095.30 GWh in the first period, 3098.02, 27697.53, 282.07, 21705.53, 1170.25 and 13402.80 GWh in the second period, 23435.90, 20358.77, 282.072, 21705.53, 1170.25, 22710.30 GWh in the third period. Moreover, the capacity expansion pattern also differs greatly from optimal ratio model shown in figures.

Fig. 7 compares the results obtained from both the MJCLP and optimal ratio models. The MJCLP model leads to slightly higher system profit than the optimal ratio model under all levels. As shown, the profits from the MJCLP approach are $\$8.28\times10^9$ under condition 1, $\$8.32\times10^9$ under condition 4, $\$8.34\times10^9$ under condition 7. However, the MJCLP model cannot optimize the ratio owing to its simplified economy objective. For the MJCLP model, the profits to carbon emission ratio are no more than 65 $/(tonne carbon emissions) under nine conditions, which is significantly lower than that from the optimal ratio model. In other words, the MJCLP model leads to lower profit-to-

emission ratio, and the optimal ratio model leads to a lower level of carbon emissions and higher optimal ratio. Compared with the MJCLP approach, the optimal ratio model can more effectively solve the sustainable EPS management and carbon mitigation problem, and better demonstrate tradeoffs and interrelationships among multiple input factors and system criteria.

Overall, the developed MJCFP approach has the following advantages over other optimization approaches. Firstly, it can balance conflicting objectives, economic profit and climate change mitigation, without modifying their original magnitudes; secondly, it can provide an effective linkage between ratio optimization problem and reflect interaction of economy and environment; thirdly, it can account for randomness of carbon emissions in constraints; fourthly, it can support in-depth analysis of the interrelationships among objective ratio, profit, and climate change risks; and lastly, it can effectively reflect not only the uncertainties but also the dynamics of end-user demands under all scenarios. The developed MJCFP approach can also be applied to other resources and environmental management problems, such as water management, waste management, and other energy management contexts.

5. Concluding remarks

A multi-stage joint-probabilistic left-hand-side chance-constrained fractional programming (MJCFP) approach was developed for electricity management and climate change mitigation under uncertainty. This method can handle ratio optimization problems associated with dynamic information, where multi-stage stochastic programming is integrated into a fractional programming framework with left-hand-side joint-probabilistic chance-constrained programming and mixed-integer linear programming. An effective solution method is proposed to tackle this integrated model. The MJCFP approach is capable of (1) balancing the conflict between two objectives, (2) reflecting different electricity generation, power allocation and capacity expansion strategies, (3) tackling uncertainty variables as probability distributions, (4) addressing left-hand-side random variables and the reliability of satisfying constraints, (5) presenting optimal solutions under different constraint violation conditions, and (6) reflecting dynamic features of the system conditions through generating scenarios of future events.

Through a real case study of the regional electric power system in Saskatchewan, the viability of the proposed method was demonstrated. With maximized system ratios under various possible user-demand scenarios and different joint and individual probabilities, the solutions obtained from the MJCFP approach are effective for electric power system management to identify electricity generation, power allocation management and capacity expansion schemes. The results indicate that reasonable solutions can incorporate various uncertainties, left-hand-side random and dynamic information into the decision-making process. Note that the approach can provide detailed analysis of the interrelationship between system optimal ratio and carbon emission constraint violation risk. In practice, the MJCFP approach can be extended to address more complicated electric power system management problems.

In Saskatchewan, conflicts between climate change mitigation and economic development can be effectively solved through the MJCFP approach without setting factors for each objective. Hence, decision makers of the regional electric power system could explore trade-off between multiple conflicting objectives, system profit and carbon emissions, which could greatly contribute to dual-objective electric power system management. Simultaneously, obtained results also indicate that this stochastic dual-objective MJCFP approach can facilitate dynamic analysis of the interactions among system optimal ratio, left-hand-side random of carbon emissions constraints and system risk.

The solutions also provide Saskatchewan several management suggestions. Primarily, in order to achieve emission reduction and economy goals, gas-fired and hydro power should be considered as main sources in a long-term period. In addition, CCS technology has a role to play since, it is able to improve emission reduction and solve fluctuation of electricity demand. Finally, in terms of future capacity expansion, renewable energy (e.g. wind power and hydro power) is highly suggested in the planning periods, which can alleviate the contradiction among electricity generation, end-users' demand, and emissions.

With dynamic and random information, this study attempts to provide an MCJFP approach for Saskatchewan to solve ratio optimization problems, involving economic profit and climate change mitigation. Thus, the provincial electric power system management strategies could achieve dual-objective optimization, and would be available for any system infeasibility due to practical problems. Although the proposed method is applied here in Saskatchewan for the first time, the results indicate that it is also applicable to other resources and environmental management problems. The MJCFP approach could also be further improved through incorporating methods of interval analysis, fuzzy sets, and game theory in its framework.

Acknowledgements

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